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Disposition effect in an Agent-based Financial Market Model

Bangwei Li[a], Wei Shang[a], Hongquan Li[a,b], Lin Huo[a], Shanying Xu[a]*

[a]*Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China*
[b] *School of Business, Hunan Normal University, Changsh 410081, China*

Abstract

Disposition effect, which refers to investors' being reluctant to realize losses, is very common in financial markets, especially in mainland China. This paper introduces the disposition effect into a multi-agent model, to research investor behavior and its impact on financial markets. As the result of computer simulation, disposition effect reveals asymmetric volatility which reflects the actual situation in mainland China market, i.e. the impact of bad news on volatility is greater than the impact of good news of the same magnitude. Sensitivity analysis shows that investors' disposition behaviour slows the release rate of news, makes market more stable around the fundamental price. Meanwhile, proper level of disposition effect can avoid some loss in investment, and make chartist get relative higher return than usual. These conclusions could hopefully offer insights and effective support for investment decision-making and policy regulation.

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Keywords: Disposition effect; Asymmetric volatility; Agent-based model

1. Introduction

In financial markets, there is a phenomenon that investors appear reluctant to realize losses; that is, investors seem to prefer selling winning stocks too early and holding losing stocks too long. This pattern has been labelled as the disposition effect by Shefrin and Statman (1985)[1] and explained with a combination of mental accounting and risk-seeking in losses. A number of researchers have demonstrated the basic effect using different investor

* Corresponding author. Tel.: +86-136-6105-6150; fax: +86-010-6265-1378.
E-mail address: xsy@iss.ac.cn.

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databases[2-4]. This work clearly documents the existence of the disposition effect. The disposition effect has also been discovered in the Finnish stock market[5], the Finnish apartment market[6], the Taiwanese stock market[7], the company stock options market[8], and the residential housing market[9].

The disposition effect in Mainland China financial market is more obvious. A large majority of Chinese investors exhibit disposition effect, and their disposition effect appears stronger[10-12]**.** That is because there is a lack of institutional investors trading in Chinese stock market, the trading values of the Shanghai and Shenzhen stock markets are contributed mostly by individual investors[13]. Such investors are called "noise traders", since they hardly have any access to inside information, irrationally act on noise as if it were information that would bring them advantages in investment[14]. These unseasoned or unduly optimistic Mainland China investors tend to exhibit disposition effect[3, 15], i.e. they are reluctant to sell the loss and then delay the release of bad news. Therefore they display the unique asymmetric volatility in Mainland China financial market: the impact of bad news (negative unexpected return) on future volatility is greater than the impact of good news (positive unexpected return) of the same magnitude[16].

Disposition effect can affect the stability of financial market. If disposition investors have private information about the future prospects of a company whose stock they hold, disposition effect may slow the rate at which this information influence the stock price[2]. Given that disposition investors ration the stock's supply, bad news travels slowly across assets trading at large capital losses, which displays the disposition effect and result in stock price's "underreaction" to news[17]. By affecting supply, the disposition effect may also contribute to market stability near prices at which substantial trading has previously taken place[2]. Some studies find that more professional and experienced investors show a smaller disposition effect than amateurs[3, 15]. And there is a negative relationship between the disposition effect and investment performance, managers of underperforming funds appear reluctant to close their losing positions, conversely, successful managers realize losses at higher rates than gains, because the past return performance tends to continue in the future[18]. On the contrary, some believe that if investors hold on their losses, their current losers will in the future outperform their current winners. Disposition-driven behaviour affects mutual fund investment styles, but does not affect mutual fund performance[19]. Locke and Mann (2005) also find no evidence of any contemporaneous measurable costs associated with disposition effect[20].

In this paper the influence of disposition effect on financial market is studied through introducing disposition behaviour into an agent-based model. Agent-based modelling is a bottom-up microcosmic approach and a research method in which some factors can be controlled like in an experiment. It is used to study systems which are composed of interacting agents and which exhibit emergent properties[1]. Applying agent-based model in financial market means using these agents' adapting, learning behaviour and interaction among them for microcosmic modelling to simulate the financial market, at the same time through micro-level experiment the market's dynamic characteristic and its cause of formation can be discovered[22]. Lux and Marchesi (1999)[23] introduced herd behaviour into multi-agent model to depict stylized fact in financial market such as volatility clustering. Westerhoff[24-26] adds transaction tax, Central bank interventions and trading halts into multi-agent model to study the regulatory policies' reaction and efficiency. Tramontana[27] uses agent-based model to explore dynamic interactions between different markets. In these existing researches, however, the disposition effect is not researched as an individual decision behaviour pattern, but as a feature of the whole market. It is important to research how the disposition effect emerges as a financial market phenomena from the prospective of individual investors' decision behaviour. On the basis of Westerhoff's agent-based financial market model[26], this paper introduces the disposition effect into the model and observes the performance of simulation market. At same time, the change of investor behaviour and the change law of market volatility are also researched through adjusting the level of disposition effect.

The paper is organized as follows: Section 2 describes the simulation model for disposition effect research. Section 3 provides descriptive analysis and properties of the simulated financial market, including stylized facts and asymmetry volatility. The sensitive analysis is presented in Section 4, and conclusions are drawn in Section 5.

2. The model

There are three types of agents in the model with respect to their trading strategies: chartist, fundamentalists and inactive traders. The agents incline to select those strategies which did well in the past and change their type accordingly. Individual agent's trading strategy of each turn is decided by its observation of the expected returns. Details of the model are as follows.

Similar to the traditional artificial financial market, the model is an indefinitely dynamic model, and there is only one risk asset in the market, the total number of risk asset is fixed without changes over time. It simulates the price adjustment process by a so-called price impact function (Farmer and Joshi 2002)[28]. The price in this market is adjusted in response to excess demand as usual. If excess demand is positive, prices rise, otherwise, price will drop. The log of the price of the asset in period t + 1 is given as:

$$p_{t+1} = p_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t \tag{1}$$

where a is an impact coefficient to the excess demand, D^C and D^F stand for orders generated by chartists and fundamentalists, and W^C and W^F denote their fractions respectively. In order to make the model closer to the real markets, add a random term α_t to (1), α_t represents other random factors such as price halting, specific market regulations, and so on. Here, it's assumed that α_t is an IID normal random variable with zero mean and constant standard deviation σ^α.

In computational finance literatures the fundamentalist and the chartist are the most common heterogeneous agents. Hommes(2006)[29] deems that fundamental analysts forecast the future price of assets and form their trading activities are based on market fundamental value, while technical analysts do not care about those factors. Technical analysis trading strategy (also known as trend-following), which indicates that this type of investors try to exploit trading information about past price pattern to forecast market trend in future. Trend-followers tend to buy assets when the prices go up and vice versa. But in fact when the prices go down investors will not always sell assets, because they have disposition effect, in order to avoid realizing the loss, they may risk choosing to continue to hold assets. Bring the limited rational investors' disposition effect into the model so that make the model closer to the real markets, here the chartists' investment strategy is set as follows

$$D_t^c = \begin{cases} 0 & if \quad p_t - p_{t-1} < f \\ b(p_t - p_{t-1}) + \beta & else \end{cases} \tag{2}$$

where f <0, when the price falls more than $|f|$, chartists continue to hold the assets, which leads to their demand equal to 0; else they choose to follow a trend. b>0, is chartists' reaction coefficient to the price trend, β_t is an IID normal random variable with mean zero and constant standard deviation σ^β, which denotes other random factors. Fundamental analysis presumes that prices may run away from fundamental values in the short run, in the long run, however, prices are expected to converge towards their fundamental values. Fundamental analysis suggests buying (selling) the asset when the price is below (above) its fundamental value. Orders due to fundamental trading rules may be formalized as

$$D_t^f = c(F_t - p_t) + \gamma_t \tag{3}$$

Where c>0, is a positive reaction parameter and F is the log of the fundamental value. Meanwhile, agents are aware of the asset's true fundamental value and we introduce a random term in the demand function, γ_t is an IID normal random variable with mean zero and constant standard deviation σ^γ. For the moment, it's assumed that the fundamental value is constant

$$F_t = F_0 \tag{4}$$

Every agent has three alternatives. Besides relying on technical and fundamental trading rules, they may also be inactive. This choice depends on the strategies' attractiveness. The more attractive a strategy, the more agents will follow it. The following fitness functions[30, 31] capture the attractiveness of the three strategies:

$$A_t^c = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^c + dA_{t-1}^c \tag{5}$$

$$A_t^f = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^f + dA_{t-1}^f \tag{6}$$

$$A_t^o = 0 \tag{7}$$

It is worth noticing that the attractiveness of a strategy depends on two components. Firstly, it relies on the performance of the specific rule during current period. Secondly, it has a memory of itself. The memory parameter $d \in [0,1]$ measures how fast current fitness is discounted for strategy selection. For d=0, the fitness equals current profits. But the larger the memory of the agents, the more strongly the fitness depends on its past performance. A_t^0 is the fitness of being inactive (exit strategy) , which is set to zero. The relative weights of the strategies are determined as follows:

$$W_t^c = \exp(eA_t^c) / (\exp(eA_t^c) + \exp(eA_t^f) + \exp(eA_t^o)) \tag{8}$$

$$W_t^f = \exp(eA_t^f) / (\exp(eA_t^c) + \exp(eA_t^f) + \exp(eA_t^o)) \tag{9}$$

$$W_t^o = \exp(eA_t^o) / (\exp(eA_t^c) + \exp(eA_t^f) + \exp(eA_t^o)) \tag{10}$$

Note that the higher the fitness of a strategy, the more agents will rely on it. Parameter $e \geq 0$ captures how sensitive the mass of traders is to selecting the most attractive strategy. The higher e, the more agents will select the strategy with the highest fitness. For e=0, all agents are divided evenly across the strategies, while for e=+∞, all agents select the strategy with the best performance. In this sense, we may interpret e as a bounded rationality parameter.

3. Results

3.1 Stylized fact

To implement the proposed model, a multi-agent artificial stock market simulation platform is developed using Matlab. Model parameters settings are determined following Westerhoff's approach[26]. Parameters' value ranges are obtained from existing empirical results[32-35], and then parameters' values are decided by a trial and error calibration, results of which are: $a = 1$, $b = 0.04$, $c = 0.04$, $d = 0.975$, $e = 300$, $F_t = 0$, $f = -0.05$, $\mathrm{var}(\alpha_t) = 0.01^2$, $\mathrm{var}(\beta_t) = 0.05^2$, $\mathrm{var}(\gamma_t) = 0.01^2$.

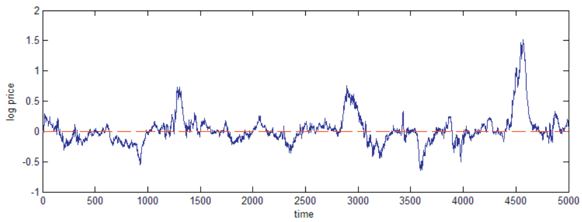

Fig.1. Time series of the log of price in simulation market

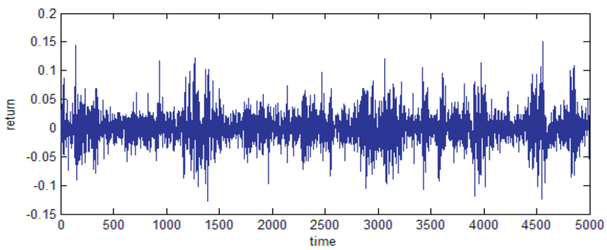

Fig. 2.Time series of return rate in simulation market

Figure 1 and figure 2 show a snapshot of the dynamics of simulation data, figure 3 and figure 4 show the autocorrelation coefficient of return and its absolute value. The statistic properties of the Shanghai composite index (SHCI) in real market from January 7, 1992 to August 1, 2013 and simulation data are compared in table 1. As can be seen from these graphs the simulation data can reappear the stylized facts in real financial market, such as bubbles and crashes, excess volatility, fat tails, random walk, volatility clustering. From table 1 both the skewness of SHCI and the skewness of simulation data are positive, which implies simulation data also can replicate the fact in China that large positive stock returns are more common than large negative ones.

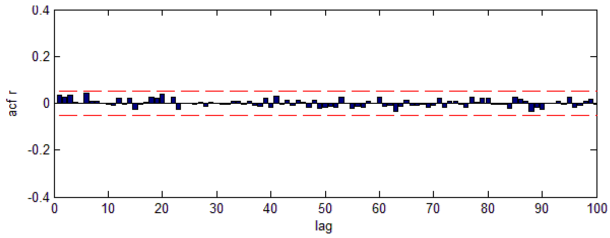

Fig.3. Auto-correlation diagram for the simulated return series

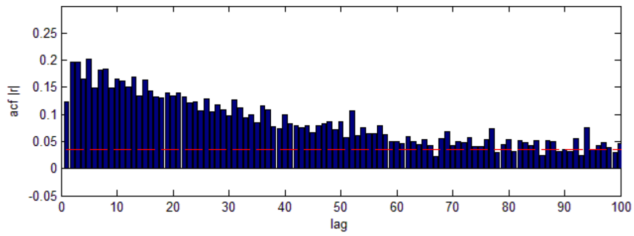

Fig.4. Auto-correlation diagram for the simulated absolute return series

Table 1 Statistical properties of SHCI returns series and simulation returns series

Sample	Mean	Variance	Skewness	Kurtosis	JarBra
SHCI	0.00026	0.0182	0.4058	19.3788	50479.20
Model	0.00003	0.0253	0.1142	5.9020	1764.966

3.2 Asymmetric Volatility

Asymmetric volatility refers to the same degree of good and bad news has different degree of influences to the volatility in financial markets. Numerous studies have demonstrated the volatility asymmetry is common in global financial markets, and in most of financial market, the impact of bad news for the market is greater than the impact of good news[36], the most obvious manifestation is that large negative stock returns are more common than large positive ones. However, due to the particularity of the Chinese market, some empirical studies find the asymmetric volatility in Chinese market shows different, the impact of good news for the market is greater than the impact of bad news. Because Chinese investors' disposition effect is more noticeable than other countries', serious disposition effect can retard the increasing of volatility which the price dropping brings. In order to study whether disposition effect will produce such asymmetric volatility, EGARCH model is used to estimate the return of simulation data here.

$$r_t = \theta_0 + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma_t^2) \tag{11}$$

$$\ln(\sigma_t^2) = \theta_1 + \theta_2 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \theta_3 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta_4 \ln(\sigma_{t-1}^2) \tag{12}$$

Where r_t is the return, the asymmetrical coefficient in conditional variance model 12 is θ_3, which is to measure the strength of the volatility asymmetry. When the estimated value $\theta_3 > 0$ is statistically significant, according to equation 12 when the residual is positive the conditional variance is larger than the one when the residual is negative, it is easy to get this kind of volatility asymmetry, the impact of bad news for the market is greater than the impact of the same degree of good news, and vice versa. Use Eviews software to build EGARCH model, and the estimated results obtained are shown in table 2.

Table 2 The estimated coefficients in EGARCH model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
θ_0	8.80E-06	0.000277	0.031821	0.9746
θ_1	-0.318795	0.029142	-10.93943	0.0000
θ_2	0.224813	0.013087	17.17865	0.0000
θ_3	0.019719	0.006580	2.996727	0.0027
θ_4	0.980689	0.003138	312.5267	0.0000

The asymmetry coefficient $\theta_3 = 0.019719 > 0$, and Prob.=0.0027, this shows that there is significant volatility asymmetry, the impact of good news for the return's volatility is greater than the impact of the same degree of bad news. When good news appears, it will have a 0.245-fold ($\theta_2 + \theta_3 \approx 0.245$) impact on the logarithm of conditional variances, but when bad news appears, it will have a 0.205-fold ($\theta_2 + \theta_3 \approx 0.205$) impact on the logarithm of conditional variances. The news impact curve is drawn in the figure 5 according to the estimated results. In this figure, the right part of the curve is steeper than the left part of the curve, which means that the positive impact would bring higher conditional variance than the equivalent negative one.

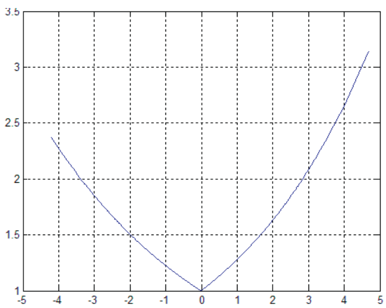

Fig.5. News impart curve

In the simulation model the main reason for emerging volatility asymmetry is disposition effect. In the market, when there is good news, asset price rises, investors adopt the corresponding investment strategies, the good news is properly released, and market volatility varies correspondingly. But when there is bad news, asset price falls, if the decline is more than $|f|$ which chartist can bear, chartist will choose to continue to hold assets rather than to sell. This prevents the release of bad news, weakens its impact, and eases the volatility, so there is the phenomenon that good news's impact would bring higher conditional variance than the equivalent bad one.

4. Sensitivity Analysis

It can be seen from the previous section that chartist's disposition behaviour can produce the volatility asymmetry in the market. In this section, the value of f is changed gradually from -0.01 to -0.15 at the step of -0.01 (the smaller f is, the weaker disposition effect is), at the same time the changes of the simulation market will be observed.

4.1 The strength of the volatility asymmetry

The values of asymmetry coefficient in EGARCH model estimated under different values of f are presented in table 3, the probability is also given. With the decrease of f, the sensitive degree of chartist to asset price falling declines, the asymmetry coefficient also becomes smaller. When f=-0.11, the coefficient has become not significant at 10% level. This further illustrates the agents' disposition effect can produce the volatility asymmetry, the more sensitive agents are to loss, the more obvious the phenomenon of volatility asymmetry is. At the same time, when f is less than a certain value (in table 3, f is less than -0.10), there has been no significant asymmetry between the effect of good news and the effect of bad news. This is because when f is small enough, the probability of the thing that the assets achieve such a low price is very low, disposition effect rarely has effect on the market.

Table 3 The asymmetry coefficient under different value of f

f	Asymmetrical coefficient	Prob.	f	Asymmetrical coefficient	Prob.
-0.01	0.450473	0	-0.09	0.014288	0.0869
-0.02	0.369855	0	-0.10	0.01225	0.0869
-0.03	0.297115	0	-0.11	0.010841	0.1354
-0.04	0.025946	0.0001	-0.12	0.009846	0.1773
-0.05	0.019719	0.0027	-0.13	0.010033	0.1695
-0.06	0.015629	0.0229	-0.14	0.009936	0.174
-0.07	0.013653	0.0468	-0.15	0.009936	0.174
-0.08	0.011983	0.0845			

4.2 The reaction speed to news

Figure 6 shows three news impact curves in three cases (f=-0.02, f=-0.05 and f=-0.1), in these curves, the one which has smaller f is steeper. News impact curve's slope reflects how sensitive the market to news, the more intensely the market reacts to the news, the steeper the curve is. Because if f is far away from 0, investors' disposition effect become weak, bad news always can get a timely release unless price falls worse than f, at this time, the market's reaction speed to news is quite fast. But if f is near to 0, investors are sensitive to loss, as long as the price falls a little more, investors will keep holding on, which mitigates the release of bad news, so at this time the market's reaction speed to news is slower. In figure 6, when f=-0.02 the left part of the curve doesn't rise, but dip down. That is because if f is very near to 0, chartists are so sensitive that they can't bear a little loss and they would choose to keep holding on even when there is a little price falling, bad news can't be released and the market fluctuation is suppressed. In this case, the bad news makes the market more smoothly.

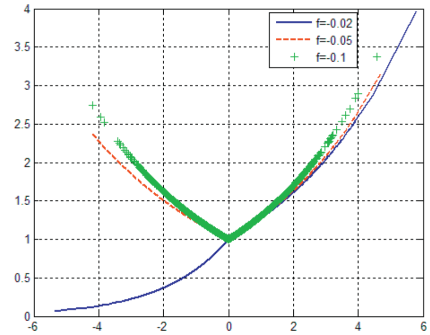

Fig. 6 News impact curves under three conditions

4.3 Strength of market volatility

In order to obtain a more precise picture of the change in dynamics, two essential statistics was defined, $dis = \frac{1}{T}\sum_{t=1}^{T}|F_t - P_t|$ is computed as a measure of the distortion in the market, and $dis = \frac{1}{T}\sum_{t=1}^{T}|P_t - P_{t-1}|$ is defined as a proxy for volatility. The length of the data set is represented by T.

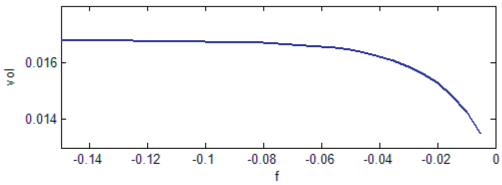

Fig. 7a Changes of vol

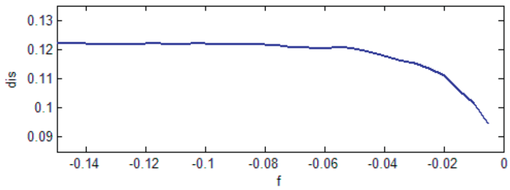

Fig. 7b Changes of dis

Figure 7 is obtained as averages over 100 simulation runs. From the figure, it's easy to get that (1) disposition effect has inhibitory effect on market swings and price deviating, when disposition effect becomes stronger (*f* closes to 0), the situation of market swings and price deviating gets to weaken. This shows that the disposition effect can improve the quality of the market. (2) As *f* becomes smaller, the degree of market volatility and price distortion rises gradually until f<-0.1, and then the volatility and distortion becomes stable and returns to the state in which there is no disposition effect in the market.

4.4 Reducing loss

The evolution of three types of investor's proportion in a simulation is presented in figure 8, where the yellow shows the proportion of those fundamental analysts, the back shows the proportion of technical analysts, and the white in the middle shows the agents without trading. W_f is the average value of W_f during a simulation, the average height of the black area.

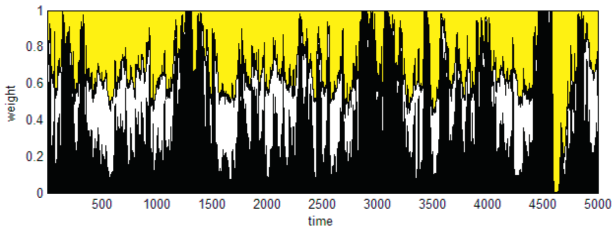

Fig. 8 The proportion of the three kind of investors

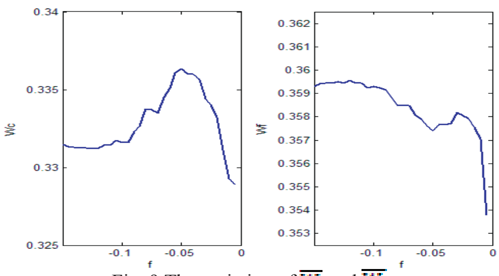

Fig. 9 The variation of $\overline{W_c}$ and $\overline{W_f}$

Figure 9 is obtained through averaging $\overline{W_c}$ and $\overline{W_f}$ in 100 times of simulation, the left part shows the change of $\overline{W_c}$, and the right part shows the change of $\overline{W_f}$. With the decrease of f, the average proportion of technical analysts gradually increases first, peaks at f=-0.05, then decreases, and levels off in the end. The proportion of fundamental analysts also gradually increases first, then decreases slightly, and then continues to increase, at last levels off. The main reasons for this situation are as follows. 1. Disposition effect slows down the release rate of bad news and retards the market's fluctuation, this reduces the profit opportunities of two types of investors, the investors leave the market and become onlookers. So when f decreases, the proportions of these two kinds of investors begin to increase. 2. If prices fall more than $|f|$, chartists will continue to hold assets, this prevents the fall in asset prices in a way. Meanwhile by mean reversion rule, the asset prices will return to its fundamental value over a period of time. So disposition effect can make investors to avoid some loss, when the loss avoided is greater than the yield missed, chartists can get higher than usual profits. This makes the proportion of chartists is higher than the proportion when there is no disposition effect.

Conclusion

In this paper the disposition effect is introduced into a multi-agent model to study its impact on financial markets. There are three types of agents with different trading strategies in the artificial asset market: chartist, fundamentalist and inactive traders. The higher return a strategy is expected to achieve, the more agents will choose it and change their type towards it. Chartists tend to buy assets when the prices go up and vice versa, but chartists have disposition effect and will continue to hold the asset if its price fallen badly. Fundamentalist would buy (or sell) the asset when the price is below (or above) its fundamental value. The inactive traders are onlookers who don't participate in the investment. The price is adjusted in response to excess demand which is determined by three kinds of investors' trading decisions.

In the simulation result chartists' disposition effect can produce such asymmetric volatility: the impact of bad news is greater than the impact of good one. This is accord with the actual situation in mainland China market. Because mainland China market investors' disposition effect is more noticeable than other countries', disposition effect can retard the increasing of volatility which the price dropping brings. In the sensitivity analysis, investors' disposition behavior slows the release rate of bad news, which has a function to inhibit the fluctuation of asset price and reduce the deviation between asset price and its fundamental value. This could further explain how disposition behavior forms the distinct asymmetry volatility of mainland China market. Disposition effect doesn't always mean loss. When investors' disposition behavior is very strong, they may earn less, but if there is a proper strength of disposition effect, investors can avoid some loss and make higher return. The proposed agent-based model and simulation results can help us to get more comprehensive understanding about disposition effect, and successfully replicate the special volatility asymmetry in mainland China market.

Acknowledgements

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